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Review

Tree species differentiation using intensity data derived from leaf-on and leaf-off airborne laser scanner data

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ABSTRACT

Tree species identification is important for a variety of natural resource management and monitoring activities including riparian buffer characterization, wildfire risk assessment, biodiversity monitoring, and wildlife habitat assessment. Intensity data recorded for each laser point in a LIDAR system is related to the spectral reflectance of the target material and thus may be useful for differentiating materials and ultimately tree species. The aim of this study is to test if LIDAR intensity data can be used to differentiate tree species. Leaf-off and leaf-on LIDAR data were obtained in the Washington Park Arboretum, Seattle, Washington, USA. Field work was conducted to measure tree locations, tree species and heights, crown base heights, and crown diameters of individual trees for eight broadleaved species and seven coniferous species. LIDAR points from individual trees were identified using the field-measured tree location. Points from adjacent trees within a crown were excluded using a procedure to separate crown overlap. Mean intensity values of laser returns within individual tree crowns were compared between species. We found that the intensity values for different species were related not only to reflective properties of the vegetation, but also to a presence or absence of foliage and the arrangement of foliage and branches within individual tree crowns. The classification results for broadleaved and coniferous species using linear discriminant function with a cross validation suggests that the classification rate was higher using leaf-off data (83.4%) than using leaf-on data (73.1%), with highest (90.6%) when combining these two LIDAR data sets. The result also indicates that different ranges of intensity values between two LIDAR datasets didn't affect the result of discriminant functions. Overall results indicate that some species and species groups can be differentiated using LIDAR intensity data and implies the potential of combining two LIDAR datasets for one study.

Contents

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1. Introduction

Tree species identification is important for a variety of natural resource management and monitoring activities including riparian buffer characterization, wildfire risk assessment, biodiversity monitoring, and wildlife habitat improvement. Conventionally an identification of tree species is conducted by a labor-intensive inventory in the field or on an interpretation of large-scale aerial photographs. However, these methods are costly, time-consuming and not applicable to large or isolated areas. Since remotely sensed data emerged and became applied in forestry, there have been efforts to classify forest types of large areas (Nelson et al., 1984). However, the use of this type of data has limitations to distinguish tree species due to the lack of high spectral resolution or large number of spectral bands.

Hyperspectral data in hundreds of spectral bands enabled a finer discrimination of spectral properties and have been applied to identifying tree species (Aardt et al., 2000; Gong et al., 1997). The spectral characteristics of tree species were studied at various scales from leaf to stand scales (Roberts et al., 2004; Williams, 1991). Spectral reflectance of tree species has been studied by different types and ages of the tree species. Rock et al. (1994) reported that second year foliage showed lower reflectance than first year foliage in the near infrared wavelength regions. Spectral reflectance of broadleaved species was found to be higher than that of coniferous species in several studies in the near-infrared wavelengths. Roberts et al. (2004) found that spectral reflectance of five broadleaved deciduous species studied was higher than five conifers studied in the near-infrared wavelength region at the branch-scale. They also found that bark has a lower spectral reflectance than leaves.

Light Detection and Ranging (LIDAR) offers an advantage over most other remote sensing technologies in its ability to capture 3-dimensional measurements over large areas. High-resolution laser scanning data is typically used to automatically generate a digital terrain model or a digital canopy model. The airborne laser scanning technique can supply forest monitoring and management planning with accuracy and efficiency. In the past, LIDAR research has focused on estimating forest structural estimates such as height, forest volume and biomass (Holmgren et al., 2003; Means et al., 2000; Naesset & Okland, 2002; Nelson et al., 1988; Popescu et al., 2002). High resolution airborne laser scanning systems now offer the possibility to isolate individual tree crowns. Most of previous studies focused on segmenting Digital Surface Model (DSM) by fitting parabolic surface (Persson et al., 2002), with local filtering and variable window size (Popescu et al., 2002), or using Watershed algorithm with local minima (Pyysalo & Hyyppa, 2002). Some researchers worked with LIDAR raw data to reduce the loss of information in the process of creating DSM from LIDAR point cloud (Brandtberg et al., 2003; Pyysalo & Hyyppa, 2002; Morsdorf et al., 2004). Pyysalo & Hyyppa (2002) used vector polygons for each individual tree crown after manually delineating points visualized on top of the DSM. Morsdorf et al. (2004) carried out segmentation using cluster analysis on the LIDAR raw data in all three coordinate dimensions. These methods were mainly intended to extract variables using coordinate data to create the structure metrics.

One variable included with most LIDAR data is a relative measure of the return signal strength associated with each return. This value, called the intensity, provides a measure of the amount of energy reflected from a target. Intensity values vary depending on the flying height, atmospheric conditions, directional reflectance properties, the reflectivity of the target, and the laser settings (Baltsavias, 1999). Most commercial LIDAR systems used for topographic mapping use lasers that emit energy in the near infrared range of the electromagnetic spectrum (often 1064 nm). Green vegetation reflects this wavelength well (Swain & Davis, 1978). As a result, LIDAR intensity data should contain information relating to forest type and condition.

In the past, LIDAR intensity data have not been used as extensively as the three dimensional structure data represented by laser returns. Some researchers have used LIDAR intensity data for classification. Song et al. (2002) applied filters to a gridded representation of intensity data and evaluated its potential to classify different materials such as asphalt, grass, roof, and trees. They concluded that LIDAR intensity can be used for land-cover classification and also reported that the relative intensity of (leaf-on) broadleaved trees was almost twice that of conifers. Brandtberg et al. (2003) used indices derived from laser reflectance data as well as height of branches to classify three deciduous species. Holmgren and Persson (2004) used two groups of variables, crown shape-based metrics and intensity-based metrics, to differentiate Norway spruce and Scots pine. These authors found that the density of crowns and gaps within the crowns affected different mean intensity values and standard deviations for the two species. A new approach using a well-defined directed graph (digraph) (Brandtberg, 2007) improved the classification accuracy markedly compared with a previous study (Brandtberg et al., 2003) using both intensity data and more reliable shape prediction. Moffiet et al. (2005) conducted exploratory data analysis to assess the potential of laser return type and return intensity as variables for classification of individual trees or forest stands according to species. They found that discrimination at the individual tree level between white cypress pine (*Callitrus glaucophylla*) and poplar box (*Eucalyptus populnca*) was not always possible, although the discrimination was reliable at the stand level. They also indicated that return intensity statistics for the forest canopy, such as average and standard deviation, were related not only to the reflective properties of the vegetation, but also to the larger scale properties of the forest such as canopy openness and the spacing and type of foliage components within individual tree crowns. Hasegawa (2006) investigated the characteristics of LIDAR intensity data for land cover classification and indicated that it is difficult for extraction of trees without supplementary information because trees have a wide intensity range and the range overlaps with the range of other height objects. Brennan and Webster (2006) utilized LIDAR height and intensity data to classify various land cover types using an object-oriented approach. They concluded that through the use of spectral and spatial attributes of LIDAR data they were able to classify a variety of land cover types using derived surfaces, image object segmentation, and rule-based classification techniques. Donoghue et al. (2007) evaluated the ability LIDAR data to estimate the proportion of species in pine/spruce mixed plantations using LIDAR height and intensity data. They used LIDAR intensity data to separate spruce and pine species and found that the coefficient of variation and LIDAR intensity data provided the most useful predictors of the proportion of spruce.

As the importance of laser scanner data increases in both scientific and commercial communities, the influences of scanning angle or flying height on the biophysical vegetation products (Ahokas et al., 2005) or on the DSM (Morsdorf et al., 2006) have been studied in European countries which has a significant topography. Growing interest in LIDAR intensity data lead to the study of intensity data depending on scan angles, flight altitude or laser path length caused by changes in the distance between the sensor and ground object. Especially, forest species classification using LIDAR intensity data may be affected by variations in laser path length due to topographic ranges. LIDAR intensity data have been investigated for their variability depending on scan angles, flight altitude or topography (Coren and Sterzai, 2006; Donoghue et al., 2007; Hasegawa, 2006). It has been found that as a scan angle increases, the variability of intensity data tended to increase, however, low scan angles had no effect on the intensity data. It should be noted that these studies were carried out using a specific laser scanner system with a specific condition for their study purposes. Hasegawa (2006) indicated that the variability of intensity data depends on target materials tested and also found that intensity correction with distance and scan angle is not always applicable, the effect of correction is not significant and consequently raw intensity value usage is justified. Previously, raw intensity data were used without corrections for the study of forest species differentiation (Brandtberg et al., 2003; Holmgren & Persson, 2004).

Recently, LIDAR intensity data were found to be directly related to spectral reflectance of the target materials (Ahokas et al., 2006). These authors studied the relationship between calibration of laser scanner intensity and known brightness targets. They concluded that intensity values were directly related to target reflectance from a variety of altitudes (200 m, 1000 m, and 3000 m) after correcting errors due to range, incidence angle (both Bidirectional Reflectance Distribution Function, BRDF, and range correction), atmospheric transmittance, attenuation using dark object addition and transmitted power (difference in Pulse Repetition Frequency, PRF, will lead to different transmitter power values). Given that most tree species classification using passively sensed data relies on the spectral (and particularly infrared) reflectance characteristics of foliage and branches, LIDAR intensity data should provide a basis to differentiate between individual tree species or species groups. Because spectral reflectance changes depending on the time of a year for deciduous species (Gates, 1980), acquiring LIDAR datasets in leaf-on and leaf-off conditions could provide additional information useful for species differentiation. By comparing intensity data from different LIDAR systems with different conditions, this study investigates the possibility of the use of multiple LIDAR data for the tree species study. By analyzing LIDAR intensity values of various tree species with different foliage characteristics, such as the presence or absence of foliage, and the spacing and type of foliage components within individual tree crowns, the relative importance of the effect of these characteristics on LIDAR-based species classification can be evaluated. For this study, it is necessary to isolate individual trees to ensure that LIDAR returns represent a single tree. Because the intensity value associated with each laser return varies depending on the target material, laser returns from coalesced crowns need to be separated even though they were positioned within crown edges.

The objective of this research is to test if multiple LIDAR intensity data can be used to differentiate individual tree species and species groups, and to investigate what factors would be related to different intensity characteristics between species.

2. Data collection

2.1. Study area

The study area is the Washington Park Arboretum, an urban green space on the shores of Lake Washington just east of downtown Seattle, WA (see Fig. 1). The area covers 93 ha and a topographic range is 15–55 m above sea level with less than 30% of slope for the majority of the site. This is a suitable field site to study forest parameters at the individual tree level because individual trees can be easily detected and measured, and in many cases, tree crowns are not significantly overlapped. We could easily collect individual samples of various deciduous and coniferous species with accurate positions at this study site.

2.2. LIDAR data

This research utilized two LIDAR datasets collected over the Arboretum. The first was acquired on August 30th, 2004 to obtain data in leaf-on conditions using an Optech ALTM 30/70 LIDAR system, operating at a flight altitude of 1200 m above the ground level configured to acquire data using a narrow scan angle of $<11°$ either side of NADIR and with a point density up to $5/m^2$. Scan pulse repetition frequency was 71 kHz and single flight line was used. The second was acquired on March 15th, 2005 to obtain data in leaf-off conditions using an Optech ALTM 3100 LIDAR system, operating at a flight altitude of 900 m above the ground level configured to acquire data using a narrow scan angle of $<10°$ either side of NADIR and with a point density up to 20 points/m^2. Scan pulse repetition frequency was 100 kHz and flight line overlap was 50%. Both systems use a 1064 nm laser and beam divergence of 0.31mrad with footprint size of 0.372 m with leaf-on data and 0.279 with leaf-off data. The x, y, z position (easting, northing and elevation) and intensity of each pulse were supplied. Up to three returns per pulse were recorded for the first leaf-on LIDAR data and up to four returns were recorded for the second leaf-off LIDAR data. The timing of the second LIDAR flight was planned so as to capture leaf-off conditions for the deciduous species. Unfortunately, the second dataset did not capture all trees in leaf-off conditions due to widely varying phenology across the wide range of species within the arboretum and unusually early bud break in 2005. Digital photos of individual trees were taken at the field site on the day of LIDAR acquisition and from an aircraft on the day after the LIDAR acquisition to enable assessments of the phenological condition of various tree species.

2.3. LIDAR-based digital terrain model

The leaf-off LIDAR dataset was used to create a digital terrain model for the study area. These data were acquired with a higher point density/square meter and using a series of overlapping flightlines. A 1×1 m resolution DTM was created using the FUSION/LDV software (McGaughey & Carson, 2003; McGaughey et al., 2004). The method for creating the LIDAR-based DTM is well-described in Andersen et al. (2006).

2.4. Species selection

We selected specific species for this study to ensure analysis of trees with different biophysical characteristics representing both deciduous and coniferous species groups. Seven coniferous species and eight broadleaved species were selected. Table 1 shows how species can be grouped depending on their characteristic leaf-structure.

2.5. Field data

Individual tree measurements were conducted at the Arboretum from April, 2005 through July, 2005. Twenty to twenty-five individual trees within each species were selected. Our purpose was to collect individual tree samples of the selected species, and so we determined the tree locations using the Arboretum map which records tree locations with the species names and conditions and field survey before determining plot locations. If over ten tree samples were

Fig. 1. Approximate location of the Washington Park Arboretum, Seattle, WA.

grouped together, this place was regarded as a plot and then we located three reference points that roughly form an equilateral triangle with 30–100 m sides using a Trimble Pro XR/XRS GPS system which is a differential GPS unit. Points were visible from one another to allow laser shots to and from each point and points were located in openings or areas with sparse vegetation cover to ensure adequate GPS operation. Individual tree locations were recorded from at least two of the triangle points to confirm accurate tree locations. If a tree within each plot didn't belong to the species selected, they were ignored. Laser rangefinder and compass were used to shoot foresights and backsights (horizontal and vertical distances and azimuth) along each side of the triangle. For the most part, isolated individual trees in open areas were selected to simplify the identification and measurement of individual trees in the LIDAR point cloud. For each tree, stem diameter was measured at 1.4 m above ground with a diameter tape and the species name was recorded. Tree height, crown base height (CBH), and crown diameter (CD) were also measured for each tree. Tree heights and CBH were measured using a clinometer and an Impulse LR laser. CBH was measured as the distance along the stem from the ground to the attachment point of the first living branch. If there is a wide-separation between this branch and the main crown, a higher and more representative branch was selected for measurement of crown base height (Holmgren & Persson, 2004). In this study, CD was measured to assist in detecting individual tree locations in the LIDAR point clouds and two perpendicular measurements were obtained. One in the north–south direction through the center of the stem was measured, and the other in the east–west direction crossing the mid- point of the north–south length. The final CD was

Table 1
Tree species used in this research.

Coniferous species			Broadleaved species		
Leaf structures		Species	Leaf structures		Species
Clustered needles	Evergreen	• *Pinus*	Opposite simple leaves		• Bigleaf maple (*Acer macrophyllum*)
	Deciduous	• Larch (*Larix*)	Alternate compound leaves		• *Sorbus*
Single needles	On woody pegs	• Spruce (*Picea*)	Alternate simple leaves	Thorns	• *Prunus*
					• *Malus*
	With flat needles	• Douglas-fir (*Pseudotsuga mensiesii*)		No thorns	• Birch (*Betula*)
		• Western hemlock (*Tsuga heterophylla*)			• Elm (*Ulmus*)
		• Redwood (*Sequoia sempervirens*)			• Oak (*Quercus*)
Scale-like leaves		• Western red cedar (*Thuja plicata*)			• *Magnolia*

Table 2
Summary of field measurements with the number of trees, mean stem diameter at breast height (DBH), mean height, mean crown base height (CBH) and mean crown diameter (CD) for each species.

Species		Number of trees	Mean DBH (cm)	Mean Height (m)	Mean CBH (m)	Mean CD (m)
Broadleaved	Birch	22	28.19	19.57	0.84	6.87
	Bigleaf maple	20	64.12	21.67	5.47	13.17
	Elm	20	29.22	15.80	3.03	9.55
	Magnolia	25	37.10	20.71	1.34	12.21
	Malus	20	17.32	7.43	0.64	7.55
	Prunus	20	22.28	6.81	1.26	7.90
	Quercus	25	41.34	21.35	2.91	11.42
	Sorbus	20	13.10	7.51	1.57	4.75
Coniferous	Cedar	23	84.72	24.95	1.21	10.07
	Douglas-fir	20	59.21	27.18	7.12	8.12
	Larch	25	62.35	24.81	2.23	12.27
	Pinus	25	51.69	23.04	3.66	7.94
	Redwood	20	71.27	21.76	0.34	8.63
	Spruce	22	33.82	16.97	0.15	6.58
	Western hemlock	20	13.86	33.53	2.59	10.85

Note: The number of trees per species was changed depending on how many trees were clearly detected at the office.

the average of the two perpendicular measurements. A summary of field measurements for each species is shown in Table 2.

In the office, all GPS data were post processed to obtain differentially corrected coordinates. The custom trilateration program was used with the GPS locations and the distances and azimuths to the triangle points to obtain final point locations and the local magnetic declination. The distance and azimuth shots to other points of interest using the corrected triangle locations and local magnetic declination were processed.

3. Methods

3.1. Isolation of individual tree crowns

Individual trees were initially detected with the aid of field-measured stem location using planimetric (x–y) position of the stem, tree height and crown diameter using FUSION/LDV software which displayed the LIDAR return data near the approximate tree location (Fig. 2). Even though tree stems were not correctly positioned relative to the point cloud data, field-measured tree height and crown diameter helped the detection of trees when the x,y positioning errors are within 2 m. In case that tree locations were still vague, these samples were ignored from the dataset. Initially collected numbers of trees were changed depending on how many trees were clearly detected at the office. A location for each tree was assigned and the approximate crown diameter was manually measured using the LIDAR point cloud. McGaughey et al. (2004) discussed the limitations of using this software when identifying and isolating individual trees in areas where tree crowns overlapped. Although isolated trees were selected for measurement in the field, some tree crowns overlapped with other tree crowns. Laser returns representing the ground surface and those less than 1 m above the ground surface were omitted from the data subsets to remove the effects of laser points from the groundcover and low vegetation. The remaining laser points are called non-ground laser points. Next, the laser points within the individual tree crowns were isolated within a cylinder defined by the field-measured location and crown diameter for each tree. Crown base height was calculated using

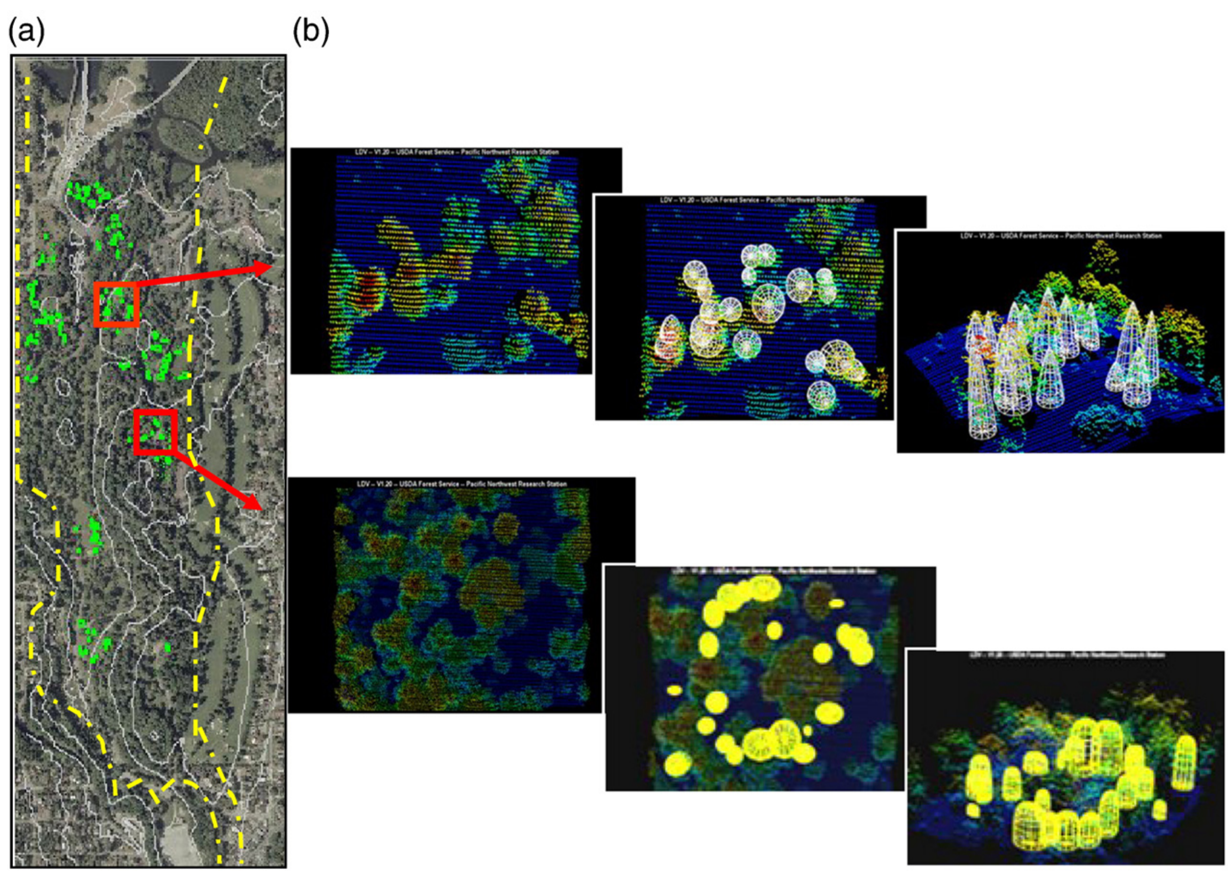

Fig. 2. Display of individual trees using FUSION/LDV software. The location of individual trees is plotted over aerial photography (a). LIDAR point clouds are displayed in the FUSION data viewer (LDV) with individual returns colored by height values (blue colors with low height levels through red colors with high height levels). Conifers are displayed using white conical cylinders shown on top of (b) and broadleaved species using yellow round top conical cylinders at the bottom of (b).

0.5 m height layers (Holmgren & Persson, 2004). Each layer that contained less than 1% of the total number of non-ground laser points within an individual tree was set to zero and the others to one. The crown base height was then set as the distance from the ground to the lowest laser data point above the highest 0-layer found.

After LIDAR point clouds were isolated within the boundary of the approximate crown diameters, a more sophisticated algorithm was applied to obtain a more precise, "pure," set of laser points belonging to each individual tree crown. When tree crowns were significantly overlapped, laser reflections from both trees are likely mixed within their crowns. It is impossible to associate a specific return with one of the trees so all laser points in the coalesced crowns should be isolated to obtain more pure reflectance information for each tree.

Naturally, a crown surface tends to get lower from a tree top (or a crown center) towards the crown edge. Coniferous species usually have one apex at or near the tree center, whereas broadleaved species often have multiple apices around the tree center. Therefore, the tree center was defined differently depending on the species: the treetop (highest point) was used for coniferous species and the center of a tree crown, as a mean value of x- and y-coordinates within a crown was used for broadleaved species. The method of evaluating distributions of LIDAR point clouds radially from the tree center to the crown edge consisted of three stages (see Fig. 3):

(1) LIDAR point clouds within the boundary of crown diameters were divided into eight, 45° radial sectors extending from the tree center to the crown edge (see Fig. 3(a)),
(2) for each sector, the horizontal distance from the tree center to the return was computed and the return height stored (see Fig. 3(b)), and
(3) the resulting list of points is sorted using the horizontal distance and a mean point height for laser points was computed at every 0.5 m horizontal distance interval starting from the tree center (see Fig. 3(b)).

The length of the radial sample of laser points varies depending on the crown radius, from a minimum measurement of 1.5 m (*Sorbus*) to the maximum of 11.5 m (*Acer macrophyllum*). The transect calculated as the computed mean height for each 0.5 m interval along the new x-axis can fall into one of three general cases. For the first case, mean point heights decrease from the tree center to the crown edge consistently. In this case, the tree was assumed to be purely isolated and all laser points were used for the later analysis (see Fig. 4(a)). For the second case, mean point heights start decreasing from the tree center but begin increasing over the last few intervals (see Fig. 4(b)). In this case, two trees were assumed to overlap around the edge of tree crowns and the intervals where mean point heights are increasing were excluded. Three different scales were applied to each sector depending on the crown size:

1) if average crown radius was less than 3 m (small crown), the last intervals were deleted up to two intervals (1 m),
2) if average crown radius was between 3 and 6 m (medium crown), the last intervals were deleted up to three intervals (1.5 m), and
3) if average crown radius was over 6 m (large crown), the last intervals were deleted up to four intervals (2 m).

For the third case, mean point heights start decreasing from the tree center but begin increasing in the middle of the transect (see Fig. 4(c)). In this case, there are two possibilities: one possibility is that foliage is irregularly distributed within the crown, increasing the mean point height through the middle of the transect, and the other is that two tree crowns overlap. For cases where the foliage is irregularly distributed, the tree crown can be considered as being isolated and all laser points were used for later analysis. For cases where tree crowns overlap, laser points within the overlap area should be deleted. If the trend of mean point heights increases in the middle of the transect consecutively over a certain distance threshold, the tree crown was assumed to overlap in that sector and this sector was excluded (see Fig. 3(c)): 1) if the mean point heights increase for more than two intervals (1 m) in the small crown, the sector was excluded, 2) if the mean point heights increase for more than three intervals (1.5 m) in the medium crown, the sector was excluded, and 3) if the mean point heights increase for more than four intervals (2 m) in the large crown, the sector was excluded. The task of analyzing and excluding laser points belonging to neighborhood trees was conducted using the Interactive Data Language (IDL) from Research Systems, Inc.

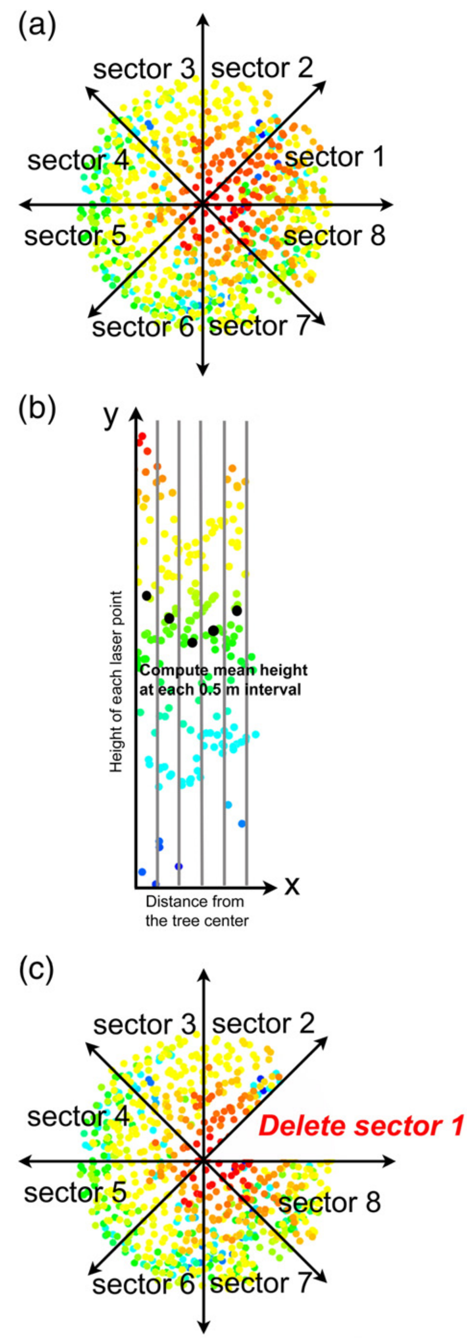

Fig. 3. The subset of LIDAR returns representing a single tree is evaluated using a series of radial profiles. (a) shows an overhead view of isolated individual tree crowns overlaid by eight, 45°radial sectors, (b) shows a horizontal view of sector 1 and illustrates the method used to determine the presence of overlapping tree crowns by evaluating the computed mean point heights for laser returns at each 0.5 m interval, from the tree center to the crown edge, and (c) shows final subset after sector 1 was deleted because there was an adjacent tree within this sector. LIDAR point clouds are colored by height values (blue colors with low height levels through red colors with high height levels).

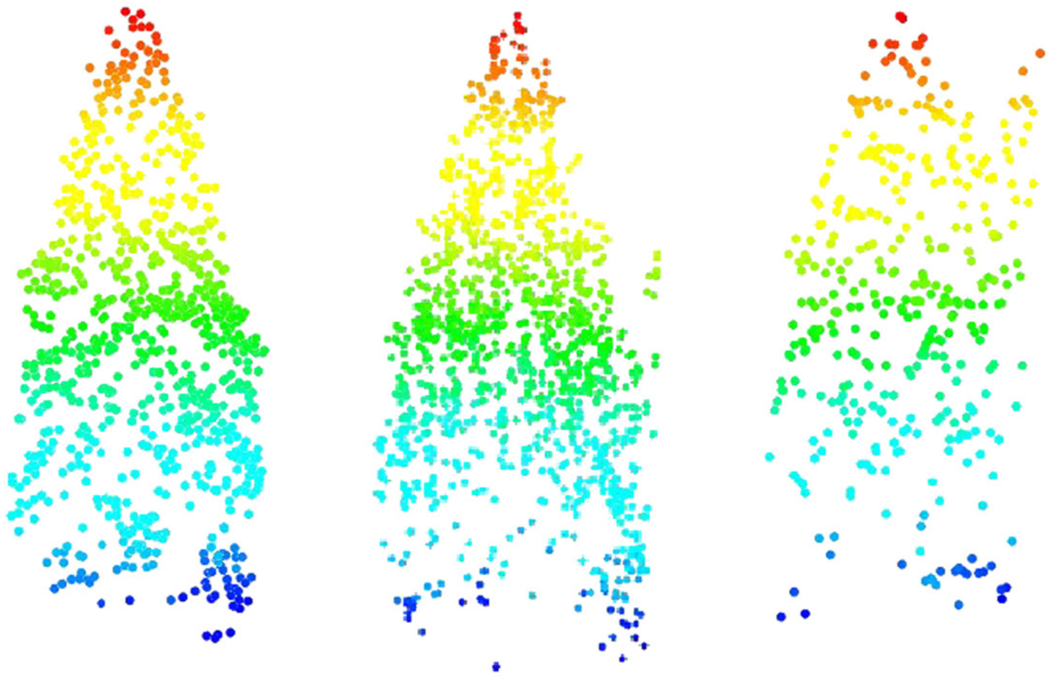

Fig. 4. Isolated individual tree crowns fall into one of three cases. A tree crown is not overlapped (a), a tree crown is slightly overlapped (b), and a tree crown is severely overlapped (c) with other trees. LIDAR point clouds are colored by height values (blue colors with low height levels through red colors with high height levels).

3.2. Computation of variables

Using laser points within each crown, variables were computed to analyze intensity data for each tree. All variables were derived using laser returns that were located above the crown base height. Mean intensity values were computed using returns representing the entire crown, upper crown and crown surface within each tree crown in both leaf-on and leaf-off datasets. The role of upper canopy to estimate forest stand level parameters has been emphasized (Popescu et al., 2002) and laser returns from the upper crown are less affected by overlapped areas than those from the entire crown. The uppermost 3 m of the crown observed in the field was mostly open in this dataset. Therefore, an upper crown was defined as laser points within 3 m (vertical distance) of the highest laser point. Some individual trees of *Prunus*, *Malus* and *Sorbus* had crown lengths less than 3 m. In these cases, laser points for the entire crown were used for the upper crown.

Laser points representing the crown surface were extracted after creating a canopy surface model using FUSION/LDV software. A 0.5×0.5 m grid was overlaid onto the point data. Within each grid cell, the elevation of the highest laser point was assigned to the center of the grid cell. The resulting surface model drapes over the laser points. However, the surface may be slightly lower than many of the highest returns since the horizontal location of the grid cell center will not be the same as the location of the highest points. Returns close to the crown surface are more likely to represent leaves in the leaf-on conditions, and therefore the intensity of the crown surface would represent leaf reflectance values well. Attributes of laser returns within 1 m and 0.5 m of the surface were compared to obtain samples containing returns representing foliage without eliminating too many laser points. The difference between the mean intensity values computed using returns within the 1 m and 0.5 m buffers were compared and found to be nearly equal. To maintain a large number of returns for analysis, the 1 m buffer was used for computing variables.

In most cases, first returns have the highest intensity values when compared to other returns in the same pulse. Intensity values for first returns are most easily interpreted since they represent a direct, albeit uncalibrated, measurement of the reflectivity of the target material (McGaughey et al., 2008). Mean first return intensity values were computed for the entire crown, upper crown and the crown surface. To compare the variability of intensity among species, coefficient of variation (CV) was computed. The CV, defined as the ratio of the standard deviation to the mean, is useful when comparing variability between data with different means. The following nine variables were derived in leaf-on and leaf-off datasets using isolated laser returns within each crown: mean intensity values for the entire crown using all returns (entire_all), mean intensity values for the entire crown using first returns (entire_1), mean intensity values for the upper crown using all returns (upper_all), mean intensity values for the upper crown using first returns (upper_1), mean intensity values for the crown surface using all returns (surface_all), mean intensity values for the crown surface using first returns (surface_1), coefficient of variation of all return intensity for the entire crown (cv_all), coefficient of variation of first return intensity for the entire crown (cv_1), and proportion of first returns (prop_1).

3.3. Scaling

Because a topographic range of this study site is not significant and scan angles are narrow (<11° off-nadir) for both datasets, raw intensity data were used without additional radiometric calibration at the first step. Next, we randomly extracted multiple samples of man-made objects whose conditions are considered to be constant between the two LIDAR datasets and compared their intensity values for each sample. We collected 11 samples from paved surfaces and roof tops, respectively and compared their intensity values using box plots. The box plot results showed that the variability across the samples is constant for each LIDAR dataset albeit the ranges of intensity values are different, meaning that two LIDAR datasets are comparable. Next, we computed the ratio of the leaf-off to leaf-on medians for each sample and used the average ratio to scale the leaf-on intensity medians. Finally, we gained a scaling factor of 16.43949 to multiply the leaf-on data.

3.4. Analysis methods

Pearson's Product Moment Correlation Coefficients were computed to find the correlations between variables with leaf-on and leaf-off datasets, respectively.

To compare mean intensity values among species, entire crown mean intensity values using all returns (entire_all) and first returns (entire_1) were compared for each species. Also, mean intensity values for different crown portions were compared among species. Entire crown mean intensity data using the first returns (entire_1) in leaf-on data were multiplied by a scaling factor, 16.43949 and compared with those in leaf-off data using a box plot.

Principal component analysis (PCA) was conducted to determine a subset of the original variables which contains, in some sense, virtually all the information available in the complete set of these variables (Everitt & Dunn, 2001). The size of the subset of original variables to be retained was determined by the number of components (Jolliffe, 2002). Jolliffe (2002) suggested to retain components extracted from a correlation matrix whose associated Eigen values are greater than 0.7. Each variable is selected, one associated with each component, as the one not already chosen which has the greatest absolute coefficient value on the component. In this study, all the original variables in both leaf-on and leaf-off datasets were used for the PCA to select a subset of variables using the *r* statistical package.

For leaf-on data, three variables were selected according to the criteria; mean intensity values for the entire crown using first returns (entire_1), coefficient of variation of all return intensity for the entire crown (cv_all), and proportion of first returns (prop_1). For leaf-off data, three variables were selected. Two variables were same as leaf-on data (entire_1 and prop_1), and the other variable was coefficient of variation of first return intensity for the entire crown (cv_1). However, it will be more useful to use the same subset of the variables to compare two LIDAR datasets more directly. Because first return analysis will be more direct and easier to interpret than all return analysis, we used cv_1 for both datasets. Finally, three variables, entire_1, cv_1, and prop_1 were used for both LIDAR datasets.

A simple tree species classification test for broadleaved and coniferous species was performed on the selected subset of the original variables using a classical linear discriminant function. To evaluate the performance of a linear discriminant function, the function was applied to the data from which it was derived and calculated the misclassification rate. In this study, an improved estimate of the misclassification rate of a discriminant function, so called, leaving-one-out method was used in which the discriminant function is derived from just *n*-1 members of the sample and then used to classify the member not included. The process is carried out *n* times, leaving out each sample member in turn (Everitt & Dunn, 2001). The percentage of the correctly classified rate was calculated; (1-misclassification rate)%. This classification method was performed on the three different datasets, leaf-on, leaf-off and combined one and the results were compared. For leaf-on and leaf-off data analysis, the three variables selected (entire_1, cv_1 and prop_1) were used respectively and for the combined data analysis, six variables including two subsets of variables were used.

Also, a subset of the original species which represents deciduous broadleaved and evergreen coniferous species by excluding three flowery species, *Magnolia*, *Malus*, and *Prunus* and one deciduous conifer, *Larix* was tested using the same classification method and the results were compared with those using all original species.

4. Results

4.1. Crown overlap analysis

The result of applying the process of untangling crown overlap is shown in Table 3 indicated with the number of trees falling into three cases: case 1–non-overlap, case 2–overlap at the crown edge, and case 3–significantly overlap. Totally, 147 trees out of 223 trees (case 1) were not overlapped, nine trees were slightly overlapped at the crown edge (case 2), and 67 trees were significantly overlapped (case 3).

Table 3
The result of a crown overlap analysis with the number of trees with and without crown overlap.

	Non-overlapped	Overlapped		
	Case 1	Case 2	Case 3	Total
# of trees	147	8	67	223
Proportion of # of trees	0.66	0.04	0.3	1

Note: Case 2 indicates crowns overlapped at the edge and case 3 indicates crowns significantly overlapped.

It was obvious to find the different mean intensity values between overlapped and non-overlapped crowns within the same deciduous trees in leaf-off data before applying this method. The boxplot results using the entire crown with the first returns comparing mean intensity values among species before and after applying the method of untangling crown overlap is shown in Fig. 5. The mean intensity values became similar between overlapped and non-overlapped trees after adjusting overlapped tree crowns using this method. For example, the mean intensity values for non-overlapped species, *Quercus*, *Acer macrophyllum* and *Ulmus* were 9.42, 11.26 and 10.34, respectively while those for overlapped species were 22.30, 21.54 and 17.52, respectively. When adjusting these three overlapped species using this process, the mean intensity value were changed into 9.70, 13.21 and 11.80, respectively. However, it should be noted that conifers didn't show significant differences for mean intensity values between overlapped and non-overlapped individual trees and so the application of this method didn't make significant differences after adjusting overlapped coniferous tree crowns.

The mean intensity values before and after adjusting this method for all individual trees were significantly different using Student's two sample *t*-test in both leaf-on and leaf-off datasets ($p<0.001$).

4.2. Correlations between variables

The results of Pearson's Product Moment Correlation Coefficients (r) between variables with leaf-on and leaf-off data showed that six mean intensity variables, entire_all, entire_1, upper_all, upper_1, surface_all and surface_1, were strongly positively correlated with each other with r greater than 0.88 with leaf-on data and 0.95 with leaf-off data. This result implies that all of the variables are not necessarily used for the classification analysis and needs to be reduced using appropriate method such as Principal Component Analysis.

4.3. Boxplot results

Box plots of mean intensity values for the entire crown using first returns for species with leaf off and scaled leaf-on are shown in Fig. 6.

Generally, broadleaved species showed higher mean intensity values than coniferous species with the scaled leaf-on data. Song et al. (2002) reported the same result using LIDAR intensity data. *Betula* had the lowest mean intensity values, 26.3, among species with leaf-on data probably because *Betula* has less dense crown structures than other species. Mean intensity values were affected by the density of crown structures and found to be useful to differentiate tree species (Holmgren & Persson, 2004).

In leaf-off data, *Acer macrophyllum*, *Ulmus* and *Quercus*, all of which had no foliage at the time of data acquisition, had very low mean intensity values (12.5, 11.6 and 9.6) compared with other species (the range of mean intensity values for the evergreen conifers is 36.2–47.8). Some trees of *Betula*, *Sorbus* and *Larix* had leaves that were emerging when the leaf-off data were acquired. These species had higher mean intensity values (15.7, 17.7, and 24.1) than deciduous

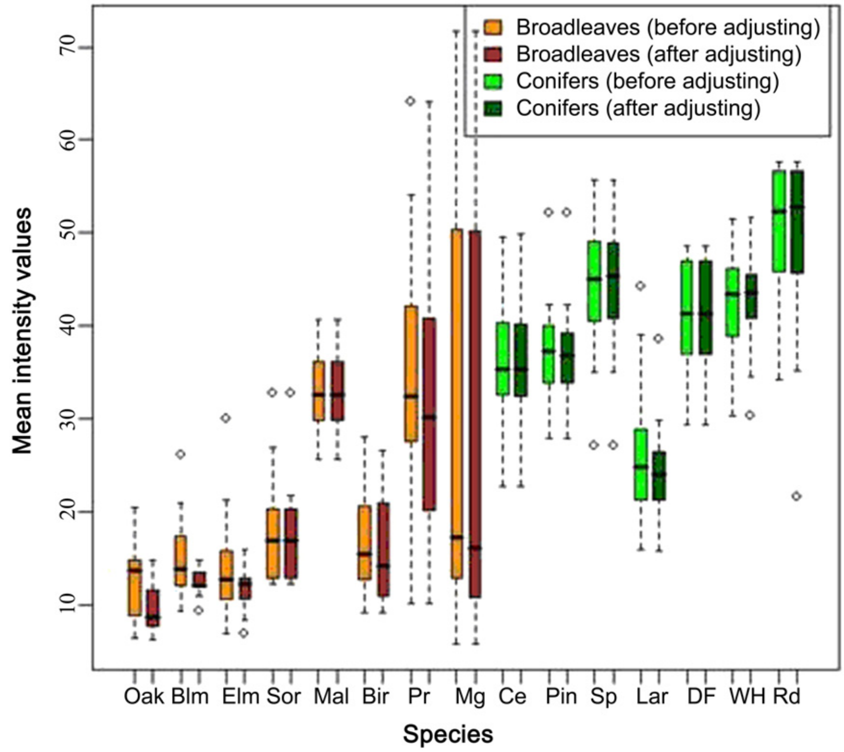

Fig. 5. Box plots of entire crown using first returns comparing mean intensity values among species before and after applying the method of untangling crown overlap with leaf-off data (Oak-*Quercus*; Blm-*Acer Macrophyllum*; Elm-*Ulmus*; Sor-*Sorbus*; Mal-*Malus*; Bir-*Betula*; Pr-*Prunus*; Mg-*Magnolia*; Ce-*Thuja plicata*; Pin-*Pinus*; Sp-*Picea*; Lar-*Larix*; DF-*Pseudotsuga menziesii*; WH-*Tsuga heterophylla*; Rd-*Sequoia sempervirens*).

trees without foliage. In addition, three species, *Prunus*, *Malus* and some individuals within *Magnolia*, which were flowering when the leaf-off data were acquired also showed higher intensity values (33.6, 32.8, and 29.8) among the broadleaved species.

With leaf-off data, *Magnolia* and *Prunus* showed high variation of mean intensity values between individual trees partly because some trees had flowers or leaves while others didn't have foliage within species. *Acer macrophyllum*, *Ulmus* and *Quercus* had very low variation

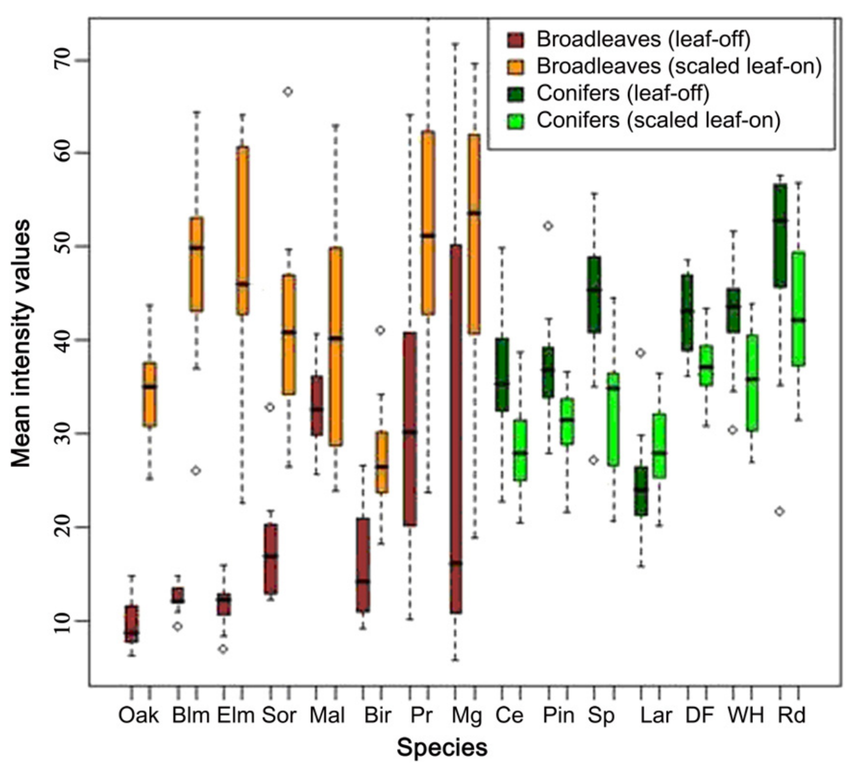

Fig. 6. Box plots of entire crown mean intensity values using first returns among species with leaf-off data and scaled leaf-on data (Oak-*Quercus*; Blm-*Acer Macrophyllum*; Elm-*Ulmus*; Sor-*Sorbus*; Mal-*Malus*; Bir-*Betula*; Pr-*Prunus*; Mg-*Magnolia*; Ce-*Thuja plicata*; Pin-*Pinus*; Sp-*Picea*; Lar-*Larix*; DF-*Pseudotsuga mensiesii*; WH-*Tsuga heterophylla*; Rd-*Sequoia sempervirens*).

Table 4
The result of a linear discriminant function for broadleaved and coniferous species for each variable with leaf-on, leaf-off and combined datasets.

Variables	Classification rate (%)		
	Leaf-on dataset	Leaf-off dataset	All datasets
Entire_all	71.2	78.5	93.3
Entire_1	69.9	79.4	91.0
Upper_all	61.3	80.3	89.7
Upper_1	60.9	80.3	90.1
Surface_all	66.3	79.4	87.0
Surface_1	68.1	79.8	87.0
Cv_all	56.2	69.0	75.4
Cv_1	69.9	71.7	82.0
Prop_1	54.2	66.9	69.8

Note: Each value was computed as a percentage of (1-misclassification rate).

of mean intensity values between individual trees with leaf-off data partly because these species had only woody materials such as branches and stems without leaves.

With the leaf-off data, the variation of mean intensity values of individual trees within *Magnolia* was very high because both deciduous and evergreen *Magnolia* were collected in this study. Some trees were flowering with or without leaves and others had no foliage at the time of the leaf-off data acquisition. Individual trees with leaves or flowers within *Magnolia* had high intensity values as much as other species with foliage whereas *Magnolia* trees without foliage had low intensity values as much as other species without foliage. Individual trees within *Acer macrophyllum*, *Ulmus* and *Quercus* had very small variation of mean intensity values with leaf-off data because they were composed of only woody material, branches and stems.

The relative magnitude of mean intensity values across coniferous species was similar between leaf-on and leaf-off datasets because these species were evergreen and had leaves in both datasets except *Larix*. *Larix* showed very low mean intensity values among conifers with leaf-off data because it is the only deciduous species among conifers in this study and therefore, its intensity values with leaf-off data were associated with woody materials.

Pseudotsuga menziesii, *Tsuga heterophylla*, *Sequoia sempervirens* and *Picea* showed higher intensity values than *Larix*, *Thuja plicata* and *Pinus* in both leaf-on and leaf-off data. This result could be related to their leaf structures. The former four species have single needles, whereas *Pinus* and *Larix* have clustered needles. Species with single needles showed higher intensity than species with clustered needles probably because clustered needles have a higher proportion of exposed branch between needle clusters, which would increase the proportion of energy reflected from branches. Among coniferous species, *Sequoia sempervirens* had the highest mean intensity values with both leaf-on and leaf-off datasets probably because of their dense leaf structures.

4.4. Mean intensity analysis among different crown portions with different returns

Generally, mean intensity values for the upper crown and crown surface were higher than those for the entire crown. This is probably because these portions of the crown contain comparatively more foliage and younger foliage than the interior of the crown. Rock et al. (1994) supports this result by reporting that second year foliage showed lower reflectance than first year foliage in near infrared wavelength regions. Mean intensity values for the upper crown or the crown surface for short species, *Malus*, *Prunus* and *Sorbus* were not consistently higher than those for the whole crown. Considering the small size of these species, 1 m buffer from the canopy surface model probably does not represent the crown surface which is expected to contain more leaves and younger leaves than the entire crown does. However, buffer thicknesses less than 1 m probably does not capture enough laser points. This result implies that analysis using the upper portion of the crown or crown surface probably does not provide useful information for these small-sized species.

4.5. Proportion of first returns

Deciduous species in the leaf-off data had low proportion of first returns, for example, *Acer macrophyllum*, *Ulmus* and *Quercus* had 0.64, 0.68 and 0.58, respectively while three short species, *Malus*, *Prunus* and *Sorbus*, had high proportions of first returns in both leaf-on and leaf-off datasets (>0.95). The proportion of first returns has been used before to characterize trees species structures (Holmgren & Persson, 2004).

4.6. The result of discriminant function

To assess the separability of broadleaved and coniferous species for each variable, linear discriminant function was performed with cross validation for leaf-on, leaf-off, and combined datasets. The result is shown in Table 4. We found that the classification rate was constant regardless of scaling intensity values for the leaf-on data. Therefore, two LIDAR datasets with different ranges of intensity values were comparable with a discriminant function. Generally, properly classified rate was higher with the variables computed using leaf-off data than those using leaf-on data. Overall classification rate for the two species groups was improved by combining leaf-on and leaf-off datasets. Among variables computed using the leaf-on dataset, mean intensity values for the entire crown using all returns (entire_all) showed the highest classification rate (71.2%) while among variables computed using the leaf-off dataset, mean intensity values for the upper crown showed the highest classification rate (80.3%). When combining leaf-on and leaf-off datasets, mean intensity values for the entire crown using all returns (entire_all) showed the highest classification rate (93.3%).

The result of classification rate using a subset of variables computed from Principal Component Analysis is shown in Table 5. The classification rate using the leaf-off dataset was higher (83.4%) than the leaf-on dataset (73.1%). When combining leaf-on and leaf-off datasets, the classification rate was raised up to (90.6%) The classification results using a subset of species group without four species, *Magnolia*, *Malus, Prunus,* and *Larix* were also compared (see Table 5). For the leaf-off data, the subset of species groups improved the classification rate up to 97.1% and for the combined datasets, up to 98.9%. The classification rate decreased for the leaf-on data (63.0%). The LIDAR dataset obtained in mid-March did not capture trees in perfect leaf-off conditions. In a normal year, trees have not flowered or developed leaves by mid-March. However, the spring of 2005 was warmer than normal and many tree species broke bud up to 2 weeks earlier than normal. Predictably, classification rate using the leaf-off data was improved by deleting these four species. This result implies that LIDAR data acquired during the winter with complete leaf-off conditions would result in better classification for broadleaved and coniferous species. The classification rate decreased without these four species in the leaf-on dataset. This is probably because foliar conditions of these species are not significantly different from the others in summer and only reduced the overall sample size.

Table 5
The result of linear discriminant function for broadleaved and coniferous species with all species and a subset of species with leaf-on, leaf-off and combined datasets.

Variables	Classification accuracy (%)		
	Leaf-on dataset	Leaf-off dataset	All datasets
Broadleaved vs. coniferous	73.1	83.4	90.6
Deciduous broadleaved vs. evergreen coniferous	63.0	97.1	98.9

5. Discussion

The analyses of two seasonal LIDAR intensity datasets for individual tree species indicate that intensity data can be used to differentiate some species and species groups.

The different ranges of intensity values for the two LIDAR datasets were predictable given that intensity values vary between LIDAR sensors and between different LIDAR flights with the same sensor. More studies are needed for the calibration of LIDAR intensity data depending on scan angles, laser path length and overlap flight lines to make it possible to use different LIDAR data for the same study site. Especially, tree species have different features depending on the time of a year and so if different seasonal LIDAR data were available, the discrimination between tree species would be more accurate than using one seasonal LIDAR data. Using intensity data for forest research is more difficult than for other studies because trees have a wide range of intensity values compared with other land cover types (Hasegawa, 2006; Song et al., 2002).

In this study, the result of discriminant functions between broadleaved and coniferous species implies that combining leaf-on and leaf-off data would result in higher separability than using LIDAR data from one season. Although the variables computed from two LIDAR datasets were compared and combined for carrying out discriminant functions albeit discriminant functions had the same values regardless of different intensity ranges, it should be noted that the two LIDAR datasets were acquired with different systems with different settings. These system effects should be considered when directly comparing different LIDAR datasets even though we scaled leaf-on data using a scaling factor computed from testing man-made objects extracted from the given LIDAR datasets. The method of computing scaling factor should be more rigorously tested for later analysis to use multiple LIDAR sets at the same study. It would be also interesting to have multiple LIDAR data sets for either the leaf-on or leaf-off conditions with same sensors to see how much variation is brought in by different data collection dates over the same conditions.

Usually, forest species classification is studied in forest stands and so the canopy overlap is more significant than the study in the Arboretum. In fact, individual tree samples were mostly isolated in this study site and laser returns within an isolated tree crown were tested if they represent the same tree. The methodology of testing the crown overlap to untangle laser returns within coalesced crowns in this study was focused on isolating laser returns associated with different species. We simply tested the validation of this method by comparing mean intensity values for overlapped individual tree crowns before and after applying this process and found that this method was useful to isolate laser returns within coalesced crowns especially for deciduous trees in leaf-off data. This method was used when a single tree was detected accurately which was possible in this study site, Arboretum, with reliable datasets to prove the exact single tree locations. Therefore, this method of detecting crown overlap might not be easily applied in dense forests with usually significant crown overlaps and with the same species types overlapped.

This study result implies that LIDAR intensity data are valuable to identify different species with different biophysical characteristics even though we didn't investigate thoroughly mean intensity values across various biophysical structures. Future study would include investigate these factors between specific tree species beyond deciduous and coniferous species groups. Structure metrics computed from each crown which is a well established variable used in forest research could be tested for the species differentiation by comparing and combining with intensity variables.

This work contributes to the growing body of literature that demonstrates the potential of LIDAR remote sensing by showing that it has a potential to differentiate tree species using intensity data with different LIDAR datasets.

6. Conclusions

Overall, our results show that LIDAR intensity data can be used to distinguish broadleaved species from conifers and to further distinguish various tree species within these broad groups. Different intensity values between species were related not only to reflective properties of the vegetation, but also to system effects from different LIDAR settings. Two different seasonal LIDAR datasets resulted in different relative intensity values among species with better separation using leaf-off data than leaf-on data, albeit with two different LIDAR sensors with different settings. Future directions for this study would include acquiring multiple LIDAR data using the same LIDAR systems with the same conditions to control for system effects. This will lead to more reliable classification results with better differentiation between tree species.

It should be noted that the study area used in this research is the Arboretum, which is not a typical forest research area and so it must be acknowledged that the approaches over dense forest stands, where forest canopy overlap is significant, individual tree species is not identified, and understory usually exits may be different.

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